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Land Use Land Cover Change Modeling using Multi-Layer Perceptron-Markov Chain; A case Study of Ahmedabad City

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Abstract: ***Geospatial technology is now widely used to capture, analyze and manage rapid urbanization in our cities. Consideration and wise use of land are essential guidelines for the advancement of human culture. Land use studies are critical to the progress of human culture. From this point of view, the evolution of land use and land cover (LULC) is a very important subject to consider. The amount of land used for each purpose is constantly evolving. Land use is affected by a number of factors such as physical, economic and social factors. Therefore, land use and land cover information (LULC) is critical for all types of natural resource management and action plans. Ahmedabad shows remarkable activities in terms of urbanization and industrialization over the past few years. It is essential to study the trends and magnitude of changes in LULC as well as the population change in the towns and villages in the Ahmedabad City for better policy and development planning. This study aims to produce a land use/land cover map of Ahmedabad City to detect the changes that have taken place over a given period and to predict the future scenario using the change detection model. In this study, remote sensing data from the Linear Imaging Self-Scanning Sensor (LISS) IV were used to detect LULC changes in the town of Ahmedabad. Imagery from 2007, 2011, 2015, 2017 and 2020 was obtained for this study. The supervised classification is carried out, five main classes have been selected for Level 1 classification and have been divided into eleven more detailed sub-classes for Level 2 classification. Analysis of changes over the period (2007-2020) revealed very dynamic exchanges across land cover classes. Predict the future LULC scenario for Ahmedabad by using Multilayer Perceptron - Markov Chain Model (MLP-MC) for the year 2033.***

Keywords: LULC Change Modelling, Image Classification, Change Detection, MLP-MC Model, Prediction

1. Introduction

LULC refers to the classification or categorization of human activities and natural landscape features. This is the classification or categorization of human activities and the natural characteristics of the landscape [26].The LULC map plays a major role in planning, managing and monitoring programs at local, regional and national levels. To ensure sustainable development and prevent random development, it is necessary to observe the ongoing process on the land use and land cover model for a certain period. It helps us to consider changes in our ecosystem and environment. Land use and land cover modelling is a growing scientific domain due to its importance in identifying results for the human environment. LULC and other land and water types Land use shows how people use the landscape, be it for development, conservation or mixed uses. Human intervention and natural phenomena such as agricultural demand and trade, ways of increasing and consuming, urbanization and economic development reduce changes in LULC. So LULC changes are a very important part of land management and are used to forecast LULC changes to sustainable use. Thus, LULC changes are a very important component of land management and are used to anticipate LULC changes to sustainable use.

Land use is influenced by many factors like physical factors which has soil fertility, soil drainage, slope angle, aspect, scenery, mineral potential etc., economic factors which has distance from markets, demand for various uses and social factors which incorporates population size, legislation, government policies and amenities. The impairment of LULC by human or natural activities raises a variety of environmental concerns such as biodiversity loss, deforestation, global warming and increased natural disasters [18].

In recent years, spatio-temporal modeling of LULC dynamics has attracted a great deal of attention in problem solving as a result of LULC alteration and conversion [15]. Using satellite image with high resolution such as LISS 4, IKONOS and Quick Bird with 1m to 5m resolution are more suitable and significant to classify LULC and will led to small scale of error [2].As far as possible, additional land cover classes should be used for detailed analysis and forecasting. Hybrid models are used to address gaps in an individual model by combining them to work in a complementary way [19].Future LULC changes have been used to provide suggestions for development of close flaw lines for future high magnitude earthquakes [23].The studies also imply that strong and consistent collaboration among states is crucial for establishing an effective regional planning framework and ensuring appropriate planned growth [13].

Since the study is spatial in nature, explicit spatial models are needed to simulate and predict changes in LULC. Accurate and timely information available from the remote sensing technologies can be efficiently used to study and analyses the past and current trends as well as to predict the future trends[6]. Number of spatially explicit models have been used to predict the future scenarios such as Markov chain (MC) model[21], artificial neural network (ANN) model[20],cellular automata (CA) model[5], logistic regression (LR) model[14], GeoMod[24], SLEUTH model[12], and conversion of land use and its effects (CLUE) model[27].

The MC model is used to describe and predict landscape shifts in the behavior of complex systems [10].It produces a transition matrix from both qualitative LULC maps from different dates. It is then used to forecast upcoming LULC maps. It also computes the probability of the cell to transit from one land use class to the other land use class from the past trends of the change in the LULC classes within a specific period which is termed as transition probability [9].But the trend to change cells is not only a function of its present state, but it is also influenced by its neighboring cells. The stand-alone MC model does not take into account the driving forces and processes that are responsible for producing the model observed in the LULC changes. As a result, it does not take into account the spatial distribution of changes [3].Therefore, the MC model is integrated with other models to better predict future LULC maps. Such hybrid models make it possible to better understand and model LULC changes [11].In the MLP-MC model, unlike the statistical model, probabilistic data models are not assumed. It includes the complex model present in the database and models the complex nonlinear relations [4].

The aim of this study is to provide a land use/land cover map of Ahmedabad City so as to detect the changes that have taken place over a given period and predict future LULC using change detection models. It covers the subsequent objective,

1) Generate LULC 1:10000 maps of the city of Ahmedabad using LISS IV satellite data for the years 2007, 2011, 2015, 2017 and 2020.
2) Analyze spatial and temporal patterns of land use and land cover to identify changes.
3) Use MLP - MC templates to predict and forecast LULC.

2. Study Area

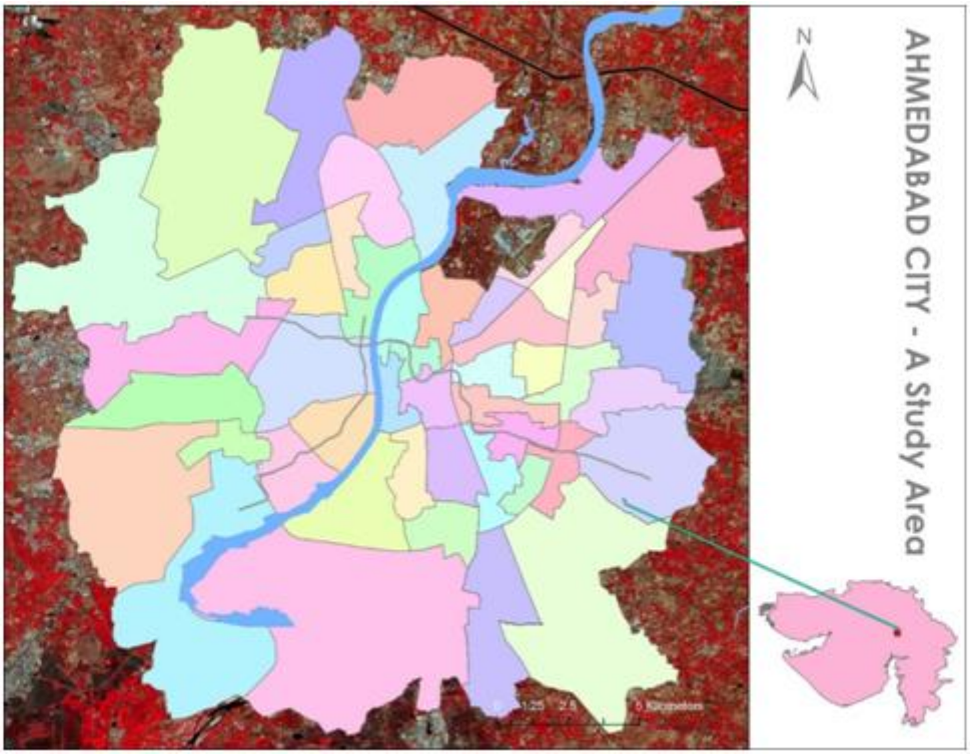

Figure 1: Study Area

The study is proposed above the city of Ahmedabad in the state of Gujarat. Ahmedabad is an urban city, densely populated and industrialized biggest city in the center of part of Gujarat in western India. Ahmedabad is divided by the Sabarmati River into two physically separate eastern and western regions. The municipal sector falls under the jurisdiction of the Ahmedabad Municipal Corporation (AMC), which covers an area of 466.2. SQ. km [25].

Ahmedabad Walled City founded by Ahmed Shah is the first Indian city to be declared a World Heritage Site. Ahmedabad City is located alongside the banks of the Sabarmati River in Gujarat more than 600 years ago. It is the largest city in the state and the 7th largest metropolis in India [7]. The city of Ahmedabad is governed by Ahmedabad Municipal Corporation (AMC), the area of approximately 466.35 km²and Greater Ahmedabad is under the jurisdiction of the Ahmedabad Urban Development Authority (AUDA) with an area of approximately 4200 sq. km. The city's population decreased from 3.31 million in 1991 to 5.8 million in 2011 (Census of India, 2011). Ahmedabad shows outstanding activities in terms of urbanisation and industrialisation in recent decades. The interaction of demographic and economic forces has translated into a highly segmented spatial growth model in terms of income class and environmental attributes. It is essential to study the trends and magnitude of changes in LULC as well as the population change in the towns and villages of the Ahmedabad City for better policy and development planning[8].A buffer zone of 2.4 km was taken around the AMC border and this entire zone of approximately 922.43 SQ.km is used as a study area to understand the future growth of the city and its land use.(Buffer is selected based on data availability).

Data used:
LISS IV images were acquired for 2007, 2011, 2015, 2017 and 2020 in order to map land use. Associated and auxiliary data sets, such as the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM), were obtained from the Geological Survey (USGS) using the website http://srtm.usgs.gov/.

The pre-processing and post image processing and analysis were carried out to enhance the quality of the images and the readability of the features LISS IV data sets were geometrically corrected, and the projection was set to Universal Transverse Mercator (UTM) projection system, Zone 43N. The spheroid and datum were referenced to WGS84. All the images were geometrically co-registered to each other using ground control points into UTM projection with geometric errors of less than one pixel, so that all the images have the same coordinate system.

Table 1: Data used

Satellite Sensor	Acquisition date	Resolution (Meter)
LISS-IV	12th April, 2007	5.8
	26th July, 2011	
	17th January,2015	
	20th October,2017	
	25th April,2020	
SRTM Digital Elevation Model	18th February, 2020	30

3. Methodology

The methodology involves collecting data that includes satellite and ancillary data. The information collected is then pre-processed.

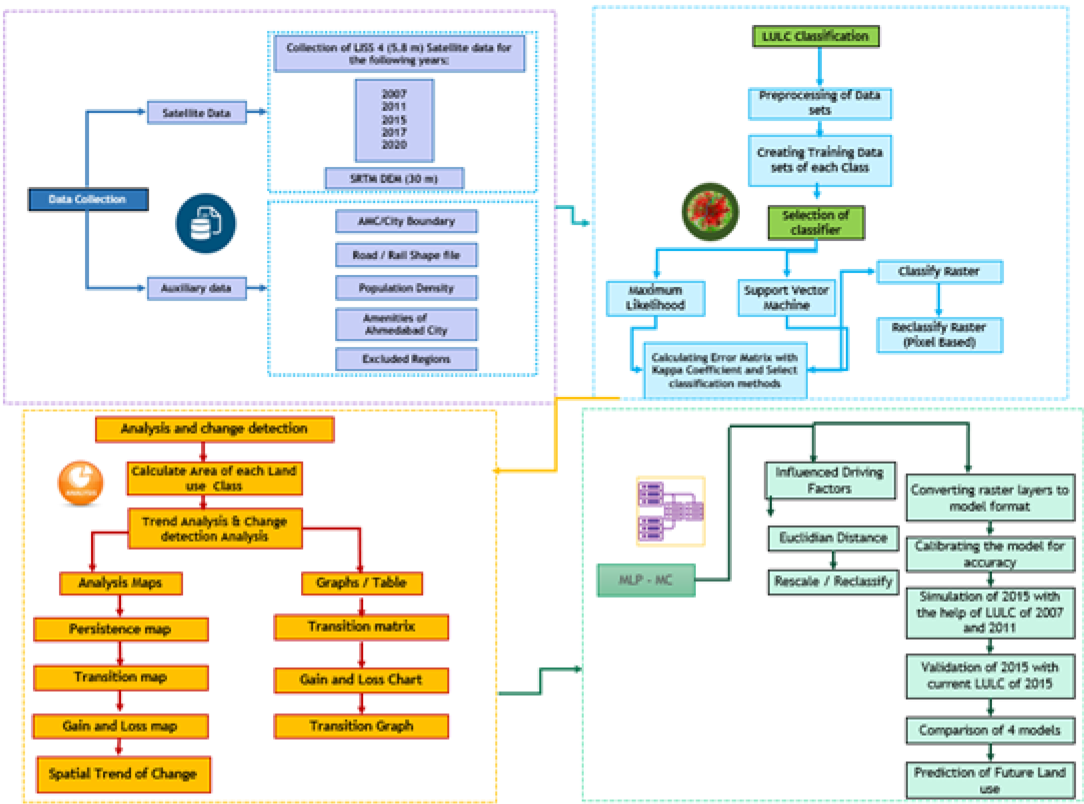

Figure 2: Methodology

Preprocessing involves stacking layers, scaling data, deleting data pixels, converting to the projected coordinate system, georeferencing, mosaic, buffer (2.4 km). At last, using the buffer study area is clipped. In the image classification performed by Two classification methods: Maximum Likelihood Classifier (MLC) and Support Vector Machine (SVM).According to the National Remote Sensing Centre (NRSC-ISRO) classes for Level 2 (Table 1). Based on the precise classification, the classification methods are selected and compare LULC for the change detection stage.

The change detection analysis maps and graphs under which different types of maps like persistence maps, transition map, gain and loss map are prepared to analyze the spatial trend of change. Based on the change detection analysis MLP-MC Model is implemented to simulate LULC for the year 2015 with support from 2007 and 2011.The result is then validated with the actual results using the kappa index stats. Subsequently, with the help of 2007 and 2020, the projection is made for the year 2033.

Table 2: Level2 Classification Classes

Built-up Dense	This class describes the land covered by closely compacted buildings.
Built-up Sparse	This class includes buildings which are dispersed or scattered that is which are not dense.
Crop Land	These are the areas withstanding crop as on the date of Satellite overpass. Cropped areas appear in bright red to red in color with varying shape and size in a contiguous to non-contiguous pattern. It includes kharif, rabi crop lands.
Fallow Land	These are the lands, which are taken up for cultivation but are temporarily allowed to rest, un-cropped for one or more season, but not less than one year.
Plantation	It includes the planting of ornamental flowering trees and plants along the city road, in parks, public places, and compound and houses both in towns and villages. It also includes the development of' nature parks' for preservation of different species of plants.
River	Rivers/streams are natural course of water flowing on the land surface along a definite channel/slope regularly or intermittently towards a sea in most cases or into a lake or an in land basin in desert areas or a marsh or another river.
Canals	Canals are artificial water course constructed for irrigation, navigation or to drain out excess water from agricultural lands.
Lakes/ Ponds	This category comprises areas with surface water in the form of ponds, lakes, tanks.
Road	A road is a thorough fare, route, or way on land between two places that has been paved or otherwise improved to allow travel by foot or by some form of conveyance.
Open Land	Open land refers to non-built-up land with no, or within significant, vegetation cover.

LULC and Change Detection

The supervised classification was carried out on the 2020 satellite image using two Support Vector Machine (SVM) and Maximum Probability Classifier (MLC) classification methods. The effective kappa coefficient, which is a statistic used to measure reliability across evaluators, was 0.7 for the MLC method and 0.9 for the SVM method. As Support Vector Machine (SVM) has given greater precision, other SVM are selected for classification.

Before Generating a final classified image, accuracy assessment is usually performed by using a reference map which is field- check or contain ground truth for the selected sample. Contribution and ground truth (Lillesand et al., 2008). The Kappa coefficient is computed using the following equation..

$$K = \frac{N\sum_{i=0}^{n} X_{ii} - \sum_{i=0}^{n} X_{i+} X_{+i}}{N^2 - \sum_{i=0}^{n} X_{i+} X_{+i}}$$

Where N is the number of observations: n is the total number of rows/columns in the error matrix; X_{ii} *represents* the number of observations in row *I; and* X_{i+} *and* X_{+I} *represents* the total number of tow I and column I respectively Overall accuracy is the ratio between the total number of correct classifications and the total number of classifications. User's accuracy defines the ratio between the number of correct classifications in a category and the total number of classifications in that category, and Producer's accuracy is the ratio between the number correctly identified in reference plots of a given category and the actual number in that reference category.

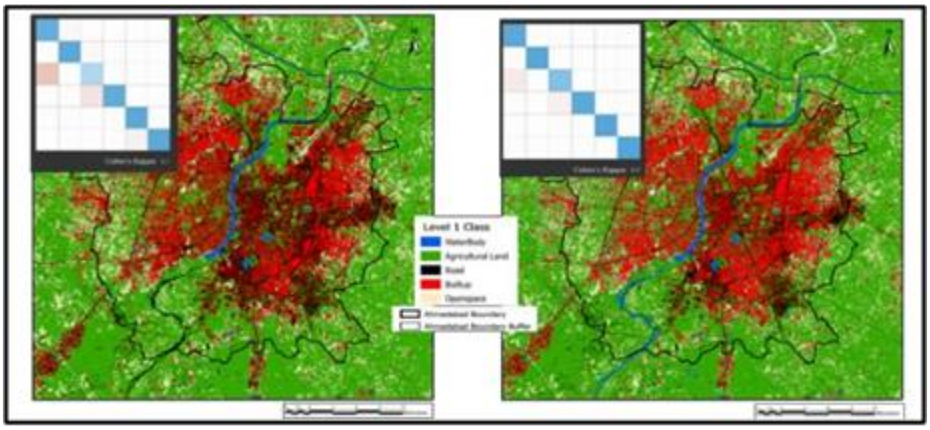

Figure 3: Classified Images using MLC and SVM

The classification class is taken according to the National Centre for Remote Sensing (NRSC-ISRO) classes for Level 2 (Table 1). The dense built-up is clearly seen in the city center and over the years the sparse built-up was increasingly out of the city boundary. To better understand and visualize, a trend graph is created as shown in Figure (4).

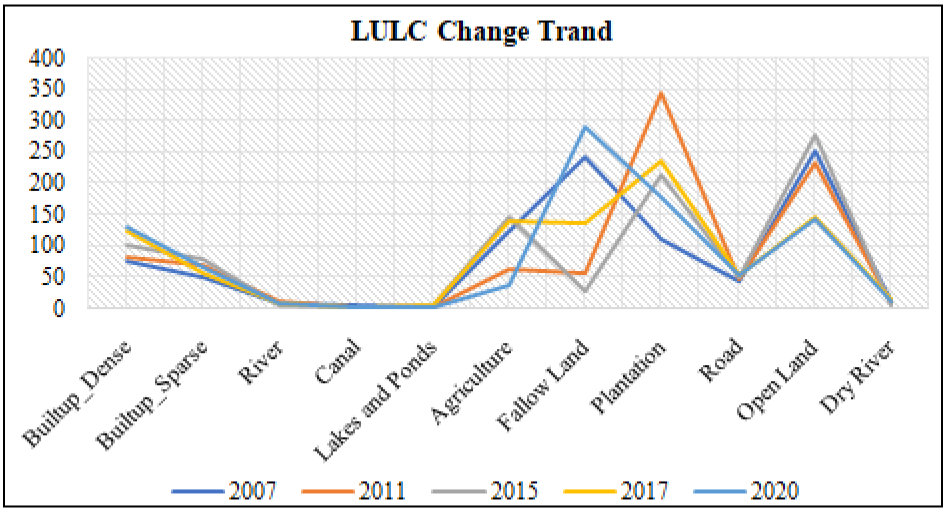

Figure 4: Level 2 Classes Trend Chart

Over the years, there has been an increase in dense/sparsely built areas and declining agricultural land. Open land has also diminished. There has not been such a dramatic change in the surface area of the water body over the period.

LULC Change Detections Modeling

Change Analysis

The Land Change Modeler (LCM) as an embedded application on IDRISI Selva is used for modeling LULC changes.

Multi-Layer Perceptron (MLP) Neural Network:

A multi-layer neural network (MLP) technique, transition potentials have been modelled by a back propagation learning algorithm (BP), which can model highly non-linear functions. A typical MLP neural network is made up of an input layer, one or more hidden layers and an output layer. Generally, one hidden layer is adequate for most studies (Lin et al., 2011; Eastman, 2012). To run the transition sub-models, the training process used samples taken from pixels that went through the transition being modeled, or pixels from persistence classes.50% of the samples were used for training and the remaining 50% were used to validate the transitional potential model. MLP in LCM is launched with an automatic training mode, which is capable of monitoring and modifing the start and end learning rates by using the sample training data (Eastman, 2012). The default values are assigned to all settings, with the exception of the number of hidden layer nodes. The default hidden layer nodes were used in the first run of the sub-model and subsequent tests were performed. If the total precision and skill score increase, the value will be doubled, otherwise the last value is selected. The performance of the MLP provided the report with the overall accuracy and rating of the skill measure. The following formula is the competency measurement of the model (Eastman, 2012)

$$S = \frac{(A - E(A))}{(1 - E(A))}$$

Where *E(A)* is excepted Accuracy and A is measured Accuracy *(E(A)* is expressed as:

$$E(A) = \frac{1}{(T + P)}$$

Where T stands for the number of transitions within the sub-model, and P stands for the number of persistence classes within the sub-model.

In order to improve the accuracy of the modelling, it is necessary to remove the variables without power by using the step-by-step analysis (Eastman, 2012).When running a sub-model with all the variables, each variable was held constant one after the other to understand which one has the least effect on the modeling. If the model skill of holding a variable constant was similar with the skill of modeling with all variables, the variable doesn't affect the model significantly and it can be removed. A change detection analysis was conducted to determine how a study area changed from two or more time periods. For this purpose, a persistence map has been created, as shown in Figure (5).The persistence map shows areas that stayed the same between 2007 and 2020.

Markov Chain (MC) Modelling

To predict the LULC change, the Markov Chain (MC) modelling was applied with the 2033 prediction date using all potential transition sub-models.In this procedure, the MC determines the amount of LULC change using land cover images from the date before the future date.It measured the amount of land available to transit from the earliest to the forecast date (Eastman 2012).

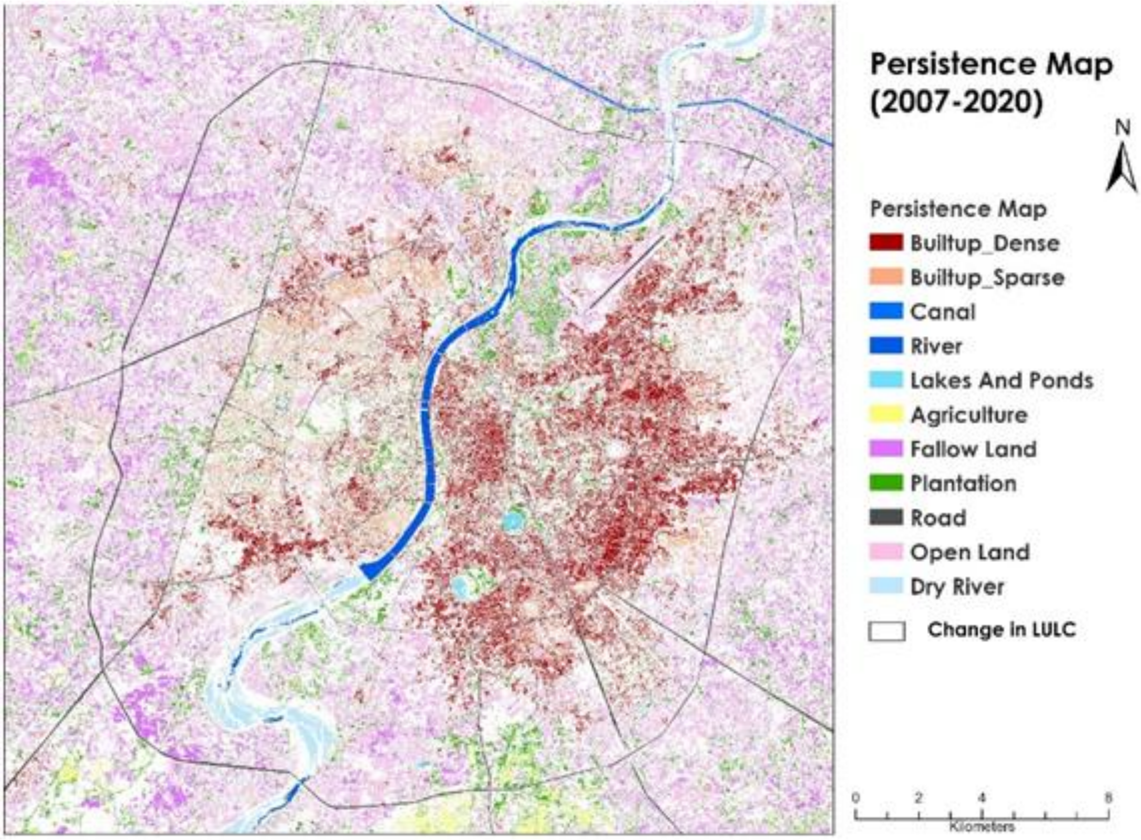

Figure 5: Persistence Map (2007-2020)

In the MC method, different grades have been applied as chain states. The value of the preceding time t 1 (X_{t1}) depends only on the value of time t (X_t), and not on the process going through X_t.It can be expressed in the following terms (Weng, 2002):

$$X_{t+1} = \mathcal{F}(X_t)$$

If the transition probabilities are tabulated in the transition matrix P, Xt-1 can be expressed and converted into graph.

Transition Matrix:

In order to better understand the transitions between one land use class and the next, a statistical table has been created.

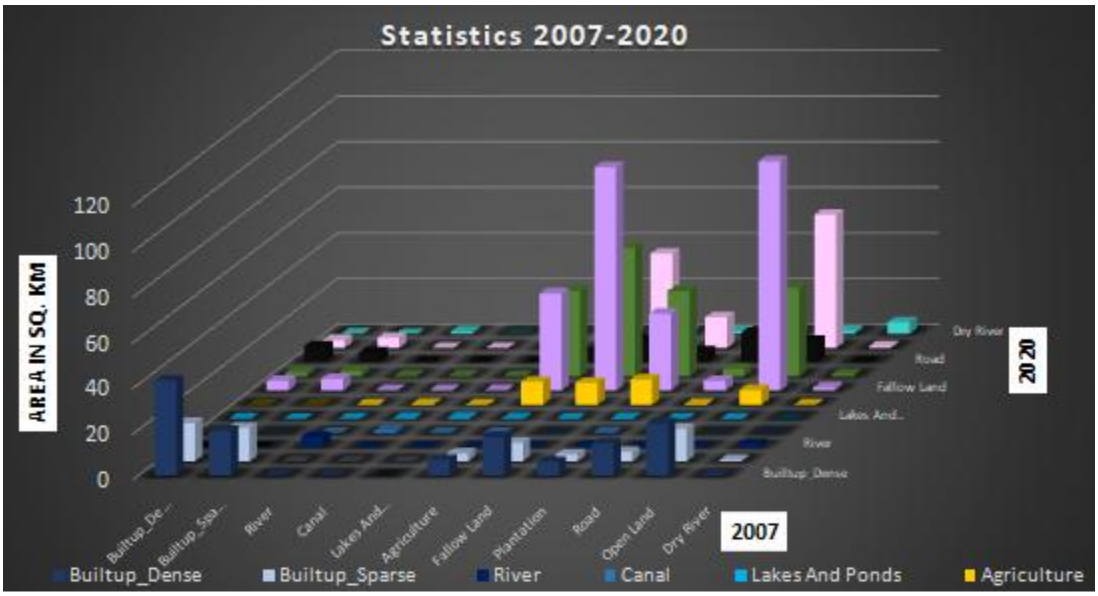

Figure 6: Transition Matrix from 2007to2020

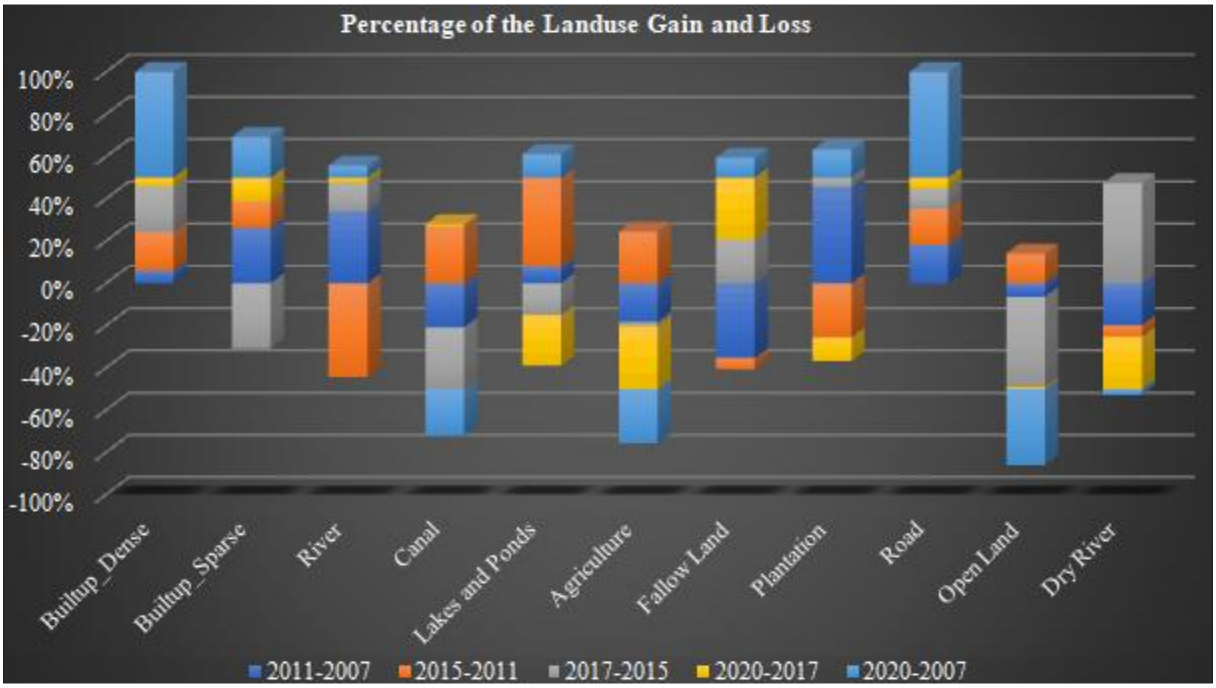

Figure 7: Percentage of the Land use Gain and Loss

Four three-dimensional statistical tables are created for four different time frames. Land use classes are indicated on the x-axis for a given year, the area of which is expressed in squares.km is shown on the Y axis and transition to another land use class for the other year is shown on the Z axis. Statistics on LULC changes indicate that in the first period, from 2007 to 2011, maximum transformation was seen in agriculture and open land. Almost 45% of open land has been converted to various LULC classes such as construction, agriculture or roads. For the second period, from 2011 to 2015, the same tendency is observed as well as an increase in built-up areas. For the 3rd period, from 2015 to 2017, there is an increase in plantation growth and a decrease in the size of the river due to the drying of the river. And in the fourth phase, from 2017 to 2020, this is the case. This LULC change statistics from the year 2007 to 2020 indicates the changes seen in the transformation from open land to various other classes i.e., Built-up, Fallow land and Roads which are 16%, 42% and 4% respectively where built-up is seen in the interior parts of the AMC boundary while fallow is seen in the outskirts of the city. Other major transformation is change in other classes to built-up i.e., Crop Land, Fallow Land and Plantation which are 8.5%, 10% and 8.5% respectively and is seen in the interior part of the city as well as on the outer parts of AMC limits in the form of liner development. The transformation of fallow land into cultivated and open land is observed, which represents 4% and 17% and occurs in the peripheries of the city.

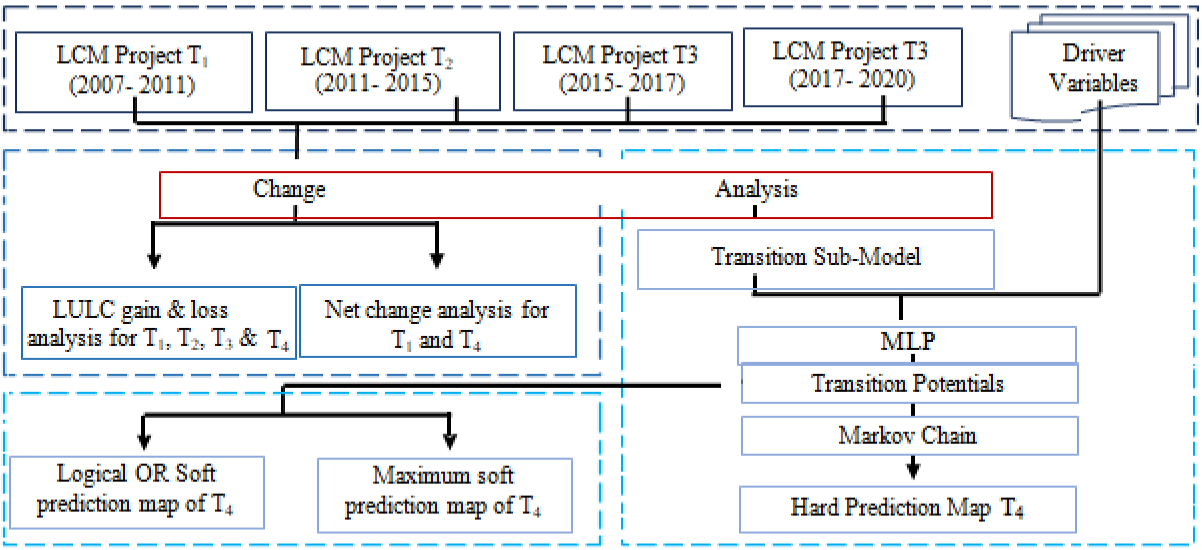

Figure 8: Process of the Multi Layer Perceptron – Markov Chain Model

The following graph (7) shows the percentage of gains and losses of the various LULC classes from 2007 to 2020.

$$X_{t+1} = X_t * P$$

The Markov Chain analysis can create a transition probabilities file which describe the probability of Land Cover Change form one period to another (Houet and Huber-Moy, 2006; Araya and Cabral, 2010). Two types of general predictions for the year 2033 were generated based on the current state of the transition potentials for each transition, including. i) the maximum soft output which shows a maximum transition probability aggregation for all transition potentials, ii) the Logical OR type calculated as ((a+b)-ab) (‘a’ and ‘b’ represent the transition potential of each sub-model) for all transitions included, which could characterize as location with different transitions. With transition probability maps, a hardware prediction LULC map was also developed for the year 2033.A multi-use land allocation algorithm was then applied to examine all transitions and generate a list of classes that included land gains and losses. While performing this allocation procedure, all modified lands within a class were assigned and superimposed to generate the output as below.

4. Results and Discussions

LULC Change Analysis

The majority of changes occur in the built-up zone as a result of the change detection analysis for the built-up zone. These results are shown in Figure (9).The red colour on the map illustrates the transition from 2007 to 2020.

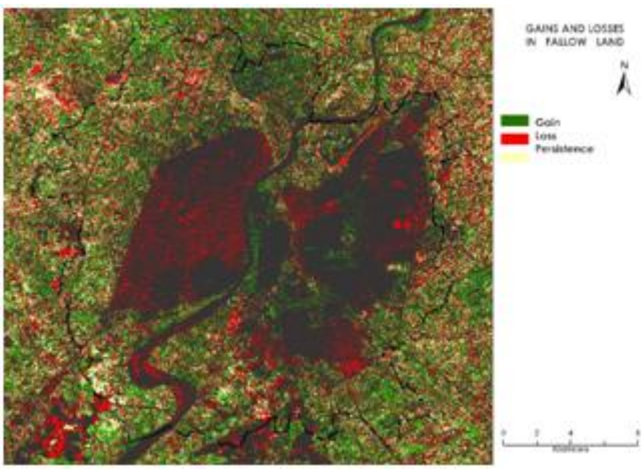

Figure 9: Gain and Loss in Fallow land during 2007-2020

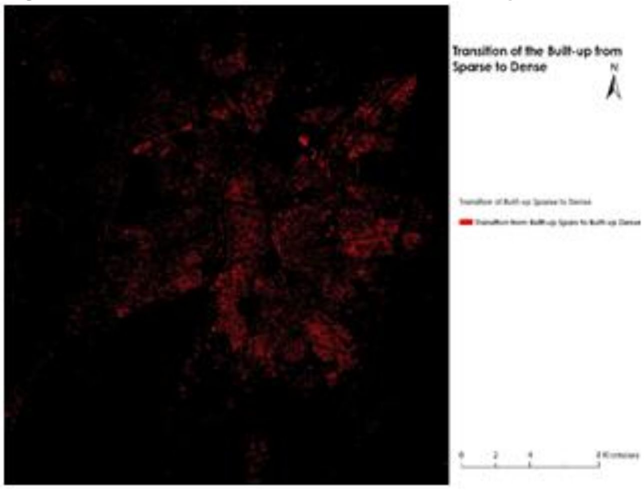

Figure 10: Transition from Built-up Sparse to Dense from 2007 to 2020

On the 2020 map, all fallow that was present in 2007 (mostly in the west) were converted to different land uses (Majorly Built-up). So, in the map shown in figure (10), red colour shows the loss in fallow land over time while the yellow colour shows no change and the green colour shows the pixels which got converted to fallow land.

Modelling Results

This study uses a hybrid model of integrated MLP and MC methods to forecast future changes in LULC over a given period of time. The software used in this project is IDRISI 17.02 Version: The Selva Edition.

It is the decisive factors which will influence the change of LULC for the city of Ahmedabad. The driving factor includes Slope, DEM, Distance from Roads, Distance from Railway, Distance from parks, Distance from Landmarks, Distance from Industries, excluded region and all these factors are rescaledbasedon1 to10forinputsin model. The first step involves a simulation process for which earlier and later land cover images of the year 2007 and 2011 are taken to simulate 2015.The second step is the change analysis where changes are assessed between Period 1 and Period 2 of the land cover maps. For this stage, the software provides a set of tools for quick evaluation of the change.

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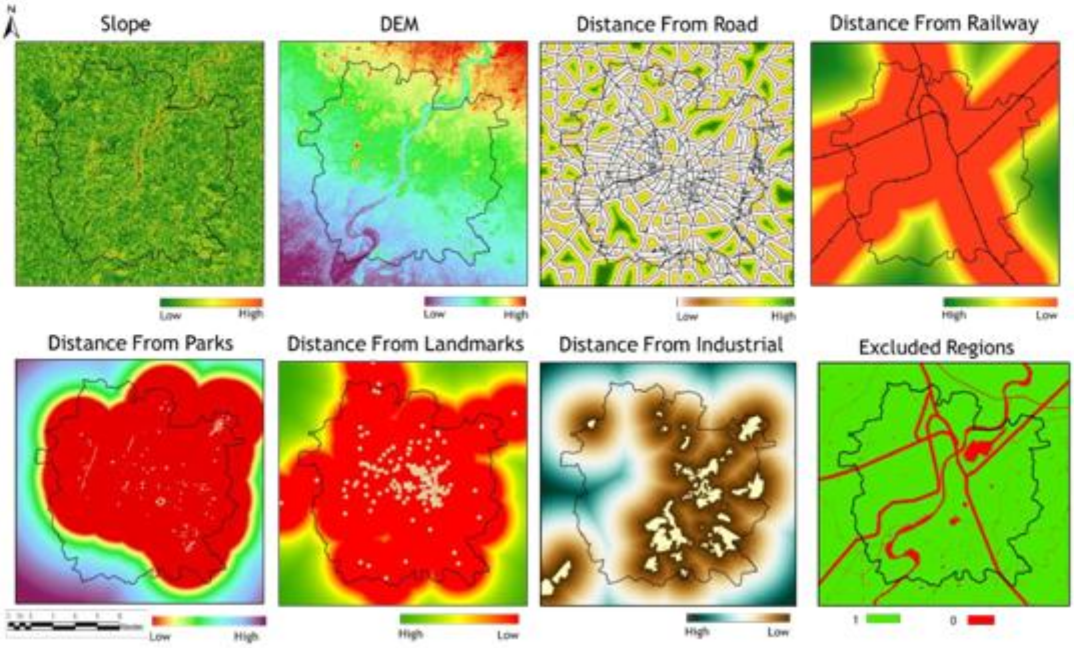

Figure 11: Driving factors used for the LULC change modelling - a) Slope, b) DEM, c) Distance from Roads, d) Distance from Railway, e) Distance from parks, f) Distance from Landmarks, g) Distance from Industries and h) Excluded region

It comprises four parameters:
1) Project Parameters: Specifies the essential file associated with land cover change analysis.
2) Change Analysis: Includes an analytical map in which the net change by category, gain and loss can be calculated between two land-based hedges.
3) Change the map to change two ground cover images. For our existing study area, 2007-2011 is used for the passage of land use classes from one to another.

Third step includes transition potential modelling which consists of transition sub model status panel, structure panel, model selection panel and transition potential panel in the software.

A transition sub-model consists of a single transition of land cover or a transition group that is believed to have certain underlying variables. Once the model is calibrated, future land use is expected.

In MLP training, it takes the sample of cases that went through the modelled transition as well as pixels that are eligible to go through the transition. The number of samples is identical for all transitional and perseverance classes. After using the training pixel with an iteration to form the network, it tests its ability to predict the correct validator class. In this case, the measure of competence and the accuracy achieved are respectively 0, 85 and 86, 57 %.

The last step (prediction) is done using a change prediction panel which consists of a change demand modeling. It calculates how much land is expected to transit from the later date of the prediction. The change allocation panel parameterizes and initiates the actual prediction process, and the validation panel allows you to determine the quality of the predicted land use map in relation to a map of reality.

This study used a hybrid model of integrated MLP and MCA methods for predicting future LULC change over a specific time. The MCA was used to simulate the number of changes using two LULC charts (2007 and 2011).Combined with MLP, the module can provide the weights of the transitions that will be embedded in the probability matrices of the Markov chain for the future prediction of the LULC change.

LULC 2015 changes are simulated based on the transition probability function of sub-type transitions and the Markov chain calculation. The intermediate output of the Markov string is a matrix with the expected amount of changes for each of the transitions considered up to the projected dates. Therefore, the prediction of the 2015 LULC map was based on the transition probability matrix of LULC changes from 2007 to 2011.The transition probability matrix is the cross tabulation of two LULC charts from different years (2007 and 2011) and is shown in Figure (11).In the transition likelihood matrix, the rows and columns represent the anterior and posterior images.

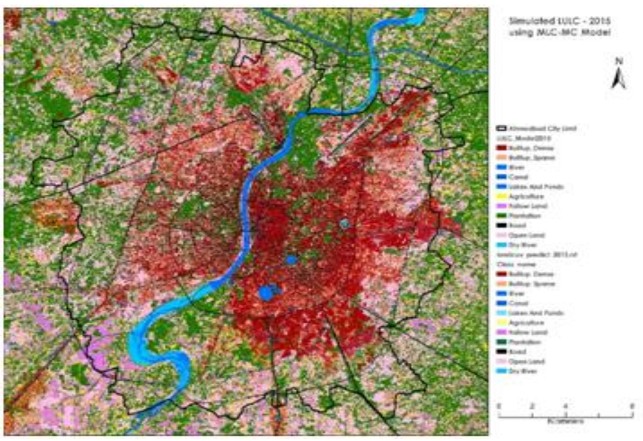

Figure 12: Simulated LULC 2015

In the preceding phase, we produced two types of results: a firm prediction (scenario) and a flexible prediction (vulnerability) for the year 2015.The hard prediction is a scenario chosen from many equally plausible scenarios; therefore, whenever there are more eligible locations for change than the actual amount of change, it is going to be very difficult to attain an accurate hard prediction. In many cases, it is important for us to have a sense of the vulnerability of land use in the study area apart from a single scenario out of many possible ones in the future. Here's where smooth prediction comes in. The soft prediction is a comprehensive vulnerability map based on the entire transition, the values of the soft prediction outputs are usually between 0 and 1.

As shown in Figure (12), the area covered by plantations and cropland is greater than the initial LULC for 2015.A similar change took place between 2007 and 2011.This is because of the modification within months of both time period images. If we look at other classes such as agglomerations and highways, there is no major change in the current LULC of 2015 and the planned LULC of 2015

Now, the hybrid model is initially compared to facilitate a valid prediction for the forthcoming LULC scenario. The aggregate kappa coefficient reached is 0.81.Once the model has been validated, the same parameters are used to predict 2033 using 2007 and 2020.Figure 19: Predicted LULC map for the year 2033

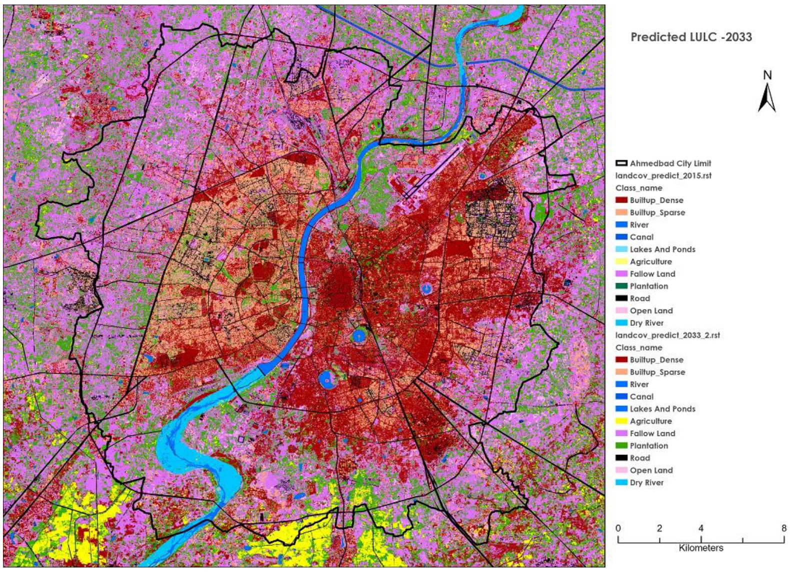

Figure 13: Predicted LULC map for the year 2033

Here, the transition potential maps, the transition probability matrices have been produced using the 2007 and 2020 LULC maps. By utilizing the LULC of2020 as the base map, the transition potential maps, and the transition probability matrices of period2007–2020, the future LULC scenarios were predicted for 2033 as shown in figure (13). Here we can say that the magnitude of the changes in LULC has been recorded high in the specific area located outside the city of Ahmedabad. The process of change has been shifted from core to periphery region and the western side of the Sabarmati river has developed in the recent past and has experienced significant transformation in LULC as compared to the eastern side of the Ahmedabad city.

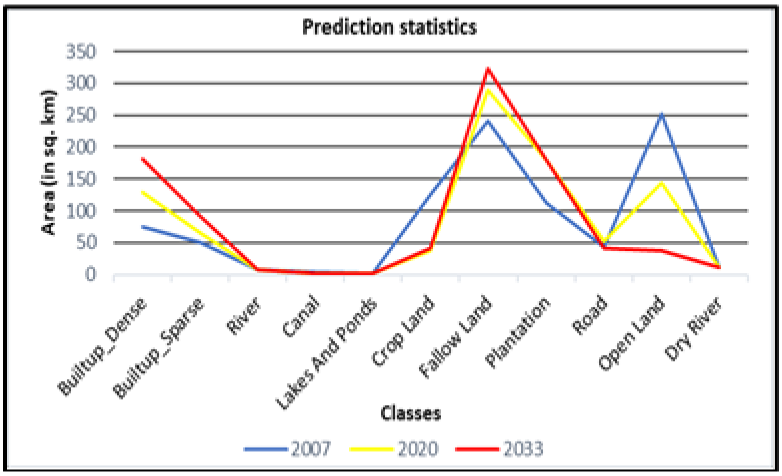

Figure 14: Trend Chart for the year 2007, 2020 and 2033

The result trends in the figure (14), we can interpret that there is a gradual increase in the built-up classes and roads because of the urbanization taking place in the city. A decrease in open land has occurred over the years as the underlying area is converted to other classes. Also, there is the decrease in the crop land and overall decrease in green cover is observed.

5. Discussion and Conclusion

In this study, a combined approach of satellite remote sensing images, GIS, and prediction models was explored to understand the spatio-temporal dynamics of LULC and future scenario in Ahmedabad city of Gujarat, India. For this purpose, LULC profiles were examined using LISS IV images of the respective years 2007, 2011, 2015, 2017 and 2020. Subsequently, the future LULC scenario was competently realized using hybrid MLP-MC models in the study area. Validation of forecast models was evaluated for 2015 using kappa index statistics. Based on the validation results, the MLP-MC model emphasized a descriptive ability for future prediction. The prediction model not only describes the quantitative and spatial changes in the past, but also the trend and amount of future changes.

The accuracy of prediction results is highly correlated with many factors. First, the accuracy of LULC maps and prediction results are negatively impacted by the moderate resolution of multi-temporal LISS IV images. Secondly, it is assumed to have a consistent transition probability in the Markov chain model. It is not yet easy to consider the unpredictable influence of other variables, such as government policy and socio-economic aspects. Thus, for better results, the image quality should be increased, and new predictive models should be developed by integrating more socio-economic and physical variables. In addition, the MLP-MC model considered only nine transitions at a time, which limits the modelling for the limited number of land cover classes. Moreover, this kind of study exhibited a high prospective to contribute towards the sustainable development and management of an area at the local as well as global level around the world.

Key research steps can be summarized as LULC mapping with a hybrid classification approach and object classification must be performed to obtain more accurate and sensitive results. The analysis of the quality and quantity of the LULC change with the post-classification technique is carried out to determine the major LULC transformations. The preparation of explanatory variables that affect the major LULC transformations is identified and the generation of transition probability maps by the MLP based on these variables is done. And the simulated 2015 LULC map was generated taking into account these factors and past LULC patterns using the MC model.

From the year 2007 to 2020, major changes are seen in the land use classes like open land and green cover which has decreased by 11% and 4% respectively and built-up area has increased by 12% of the total area. The magnitude of changes in built up was recorded high in specific areas within the city limit like Gota, Thaltej, Science City and process of change has been shifted from core to periphery region.

In addition to the increase in built-up space, the distribution of the population will also increase. This growth in population will generate demand for public services. Therefore, a more detailed analysis can be made to calculate the demand in public services based on the increase in population with the increase in built-up area. After calculating the demand, based on the existing locations of the public facilities, locations of the new public facilities can be located using the multi-criteria decision-making approach.

Comparative studies can be performed to compare more than one LULC change model and determine the most suitable model from all models used. And based on the results of the validation, the future prediction should be made using the model which indicates a better capability of the future prediction. The Level 3 Detailed Classification Study may be performed with fusion images.

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